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Estimation of machining performances using MRA, GMDH and Artificial Neural Network in Wire EDM of EN-31

G.Ugrasen[a*], H.V.Ravindra[b], G.V.Naveen Prakash[c], R.Keshavamurthy[d]

[a]*Assistant Professor, Department of Mechanical Engineering, B.M.S. College of Engineering, Bangalore, Karnataka, INDIA*
[b]*Professor, Department of Mechanical Engineering, P.E.S. College of Engineering, Mandya, Karnataka, INDIA*
[c]*Professor, Department of Mechanical Engineering Vidya Vardhaka College of Engineering, Mysore, Karnataka, INDIA*
[d]*Associate Professor, Department of Mechanical Engineering, Dayananda Sagar College of Engineering, Bangalore, Karnataka, INDIA*

Abstract

Wire Electrical Discharge Machining (WEDM) is a specialized thermal machining process capable of accurately machining parts with varying hardness or complex shapes, which have sharp edges that are very difficult to be machined by the main stream machining processes. This study outlines the development of model and its application to estimation of machining performances using Multiple Regression Analysis (MRA), Group Method Data Handling Technique (GMDH) and Artificial Neural Network (ANN). Experimentation was performed as per Taguchi's L'_{16} orthogonal array. Each experiment has been performed under different cutting conditions of pulse-on, pulse-off, current and bed speed. Among different process parameters voltage and flush rate were kept constant. Molybdenum wire having diameter of 0.18 mm was used as an electrode. Three responses namely accuracy, surface roughness, volumetric material removal rate have been considered for each experiment. Estimation and comparison of responses was carried out using MRA, GMDH and ANN.

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Keywords: WEDM, Accuracy, Surface Roughness, VMRR, MRA, GMDH, ANN.

1. Introduction

Wire cut EDM (WEDM) is a widely accepted non-traditional material removal process used to manufacture components with intricate shapes and profiles irrespective of hardness. WEDM has evolved as a simple means of making tools and dies to the best alternative of producing micro-scale parts with the highest degree of dimensional

* Corresponding author. Tel.: +91-80-26603961; fax: +91-80-26614357.
E-mail address: ugrasen.g@gmail.com

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accuracy and surface finish. Molybdenum wire is used in limited applications which require very high tensile strength to provide a reasonable load carrying capacity in small diameter wire. The effect of process parameters on the electrode wear and the amount of the erosion on wire is to be investigated experimentally in wire EDM. An attempt has been made to estimate wire wear out using multiple regression analysis and group method data handling technique.

In the past, many researchers have investigated the surface roughness is one of the most common performance measurements in machining process and an effective parameter in representing the quality of machined surface. The minimization of the machining performance measurement such as ace roughness (Ra) must be formulated in the standard mathematical model. The developed model for the machining process is a mathematical equation that shows the relationship between two parameters, process parameters (decision variables) and machining performance (responses). Fundamentally, models can be divided into three categories which are experimental models, analytical models and Artificial Intelligent (AI) based models. Experimental and analytical models can be developed by using conventional approaches such as Regression technique. While AI based models are developed using non-conventional approaches such as Artificial Neural Network, Azlan Mohd Zain et al. (2012). The development of reliable multi-objective optimization based on Gaussian process regression (GPR) to optimize the high-speed wire-cut electrical discharge machining (WEDM-HS) process, considering mean current, on-time and off-time as input features and material remove rate (MRR) and Surface Roughness (SR) as output responses empirically pointed out that handling multiple output models using an independent model cannot capture the structure in outputs that co vary, Jin Yuan, Kesheng Wang et al. (2008). The research trends in EDM on ultrasonic vibration, dry EDM machining, EDM with powder additives, EDM in water and modeling technique in predicting EDM performances, Norliana Mohd Abbas et al. (2007).

One of the main challenges in wire electrical discharge machining (WEDM) is avoiding wire breakage and unstable situations as both phenomena reduce process performance and can cause low quality components. The methodology has been followed as applied to process instability and wire breakage detection in WEDM. First, an acquisition system has been developed aimed at storing an extensive experimental database based on stable and unstable tests. The results of a preliminary analysis of a set of tests have revealed the influence on wire breakage of discharge variables, such as peak current, discharge energy and ignition delay time. Related to these discharge variables, wire breakage indicators have been defined, Cabanes et al. (2008). The vibration of the wire electrode has a significant influence on the performance and stability of the machining process. A method of computer simulation has been adopted to study the vibration of the wire electrode under the action of successive discharges, by which the effect of wire fluctuation on the distribution of the discharge points is also analyzed. The result shows that the discharge points can be distributed much more evenly along the span of the wire when an optimum condition is reached between discharge energy, discharge frequency, wire tension and wire span. Under such a condition, it is possible that the hazard of wire breaking can be avoided. The effect of electrode fluctuation on discharge state can be studied by computer simulation. In the initial break-in stage of machining, concentration of discharges will occur at discrete regions on the wire electrode, and this brings about wire breakage. The rate of discharge distribution is introduced to appreciate the distribution condition of discharge points, Guo et al. (2003). The tension control of the micro wire electrode is a key technology for the micro wire electro-discharge machining (WEDM). Based on the coupled thermo-mechanical analysis, both the three-dimensional temperature and the stress distribution in the micro wire are determined. As a result, the tension of the micro wire electrode during the WEDM process can be optimized in accordance with the discharge energy, which is sampled and fed back to the tension control system in real time. Then the development of an optimal tension control system characterized by the form of master–slaver structure makes it possible to keep the wire tension optimal in the process of WEDM. Since a relation between the inputted discharge energy and the optimal wire tension has been established, the wire tension can be real-timely adjusted by the swinging roll according to the feedback of the discharge energy, Fuzhu Han et al. (2008). Computational method for numerical control (NC) of travelling wire electric discharge machining (EDM) operation from geometric representation of a desired cut profile in terms of its contours. In generating the tool motions for cutting sections with high curvatures such as corners with small radii, a geometric path lifting method is presented that increases the machining gap and prevents gauging or wire breakage. The tool motion generated is in terms of the motion of the centre line of the wire and neglects the effects of the wire thickness as well as the gap distance on modeling the cut profile. In order to include such effects, one has to use an offset of the cut profile to generate the incremental path of the machine tool and would contribute to CAD/CAM integration for wire cut EDM operation, Wang and B. Ravani (2003). The electrode wear along the cross-section of an electrode compared to the same along its length during EDM of aluminium and mild steel using copper and brass electrodes. In an overall performance comparison of copper and brass electrodes, they found that electrode wear increases with an increase in both current and voltage, but wear along the cross-section of the electrode is more compared to the same along its length. The highest wear ratio was found during machining of steel using a brass electrode. During machining of mild steel, electrodes undergo more wear than during machining of aluminium. This is due to the fact that the thermal conductivity of aluminium is higher that of mild steel, which causes comparatively more heat energy to dissipate into the electrode during machining of mild steel, Khan (2008).

The effect and optimization of machining parameters on the kerf (cutting width) and material removal rate (MRR) in wire electrical discharge machining (WEDM) operations was investigated. The experimental studies were conducted under varying pulse duration, open circuit voltage, wire speed and dielectric flushing pressure. An optimum parameter combination for the minimum kerf and maximum MRR was obtained by using the analysis of signal-to-noise (S/N) ratio. The confirmation tests indicated that it is possible to decrease kerf and increase MRR significantly by using the proposed statistical technique, Nihat Tosun et al. (2004). Higher machining rate and better surface finish are desirable for better performance of any machining process. Comprehensive qualitative and quantitative analysis of the material removal mechanism and subsequently the development of analytical model(s) of material removal are necessary for a better understanding and to achieve the optimum process performance. Various analytical and some semi-empirical/empirical material removal models (approximately 40) for different mechanical type advanced machining processes have been comprehensively and exhaustively reviewed, Neelesh K. Jain and Vijay K. Jain (2001). The mechanism of how electromagnetic force applied to the wire electrode in wire electrical discharge machining (wire-EDM) is generated. They developed and used a two-dimensional finite element method (FEM) program to analyze the electromagnetic field taking into account electromagnetic induction. The calculated wire movement agreed with the measured wire movement when pulse current actually used in WEDM was supplied to the wire, clarifying the mechanism of electromagnetic force generation, Shunsuke Tomura and Masanori Kunieda (2009). A feed-forward neural network to estimate the work piece height and distinguish the machining condition in wire electrical discharge machining (WEDM). Experiments have been carried out to verify the effectiveness of this approach based on the on-line estimated work piece height; a rule-based strategy is proposed to maintain optimal and stable machining. According to the rule-based strategy, servo voltage and power settings can be adjusted correctly to suit the work piece profile. Experimental results demonstrate that high machining efficiency and stable machining can be achieved by means of the rule-based control strategy, Liao et al. (2002).

2. Experimental work

The experiments were performed on CONCORD DK7720C four axes CNC WED machine. The basic parts of the WED machine consist of a wire electrode, a work table, a servo control system, a power supply and dielectric supply system. The CONCORD DK7720C allows the operator to choose input parameters according to the material and height of the work piece. The WED machine has several special features. Unlike other WED machines, it uses the reusable wire technology. i.e., wire can't be thrown out once used; instead it is reused adopting the re-looping wire technology. The experimental set-up for the data acquisition is illustrated in the Fig. 1. The WEDM process generally consists of several stages, a rough cut phase, a rough cut with finishing stage, and a finishing stage. But in this WED machine only one pass is used.

The gap between wire and work piece is 0.02 mm and is constantly maintained by a computer controlled positioning system. Molybdenum wire having diameter of 0.18 mm was used as an electrode. The control factors and fixed parameters selected are as listed in Table 1. The control factors were chosen based on review of literature and experts. Each time the experiment was performed, an optimized set of input parameters was chosen. In this study, five machining parameters were used as control factors and each parameter was designed to have four levels denoted I, II, III and IV as shown in Table 1.

Fig. 1. Experimental Set-up

Table 1. Machining settings used in experiments

		Level			
Control Factors		I	II	III	IV
A	Pulse –on	16	20	24	28
B	Pulse-off	4	6	8	10
C	Current	3	4	5	6
D	Bed speed	20	25	30	35

3. Results and Discussions

3.1 Multiple Regression Analysis

The objective of multiple regression analysis is to construct a model that explains as much as possible, the variability in a dependent variable, using several independent variables. The model fit is usually a linear model, though some timer non linear models such as log-linear models are also constructed. When the model constructed is a linear model, the population regression equation is

$$Y_i = \alpha + \beta_1 X_{1i} + \ldots\ldots\ldots\ldots + \beta_m X_{mi} + e_i \tag{1}$$

Where Yi is the dependent variable and X_{1i} …………… X_{mi} are the independent variables for i^{th} data point and e_i is the error term. Error term is assumed to have zero mean. This error term is the combined effect of variables that are not considered explicitly in the equation, but have an effect on the dependent variable. The co-efficients α, β_1,……………β_m are not known and estimates of these values, designated as a, b_1…….b_m have to be determined from the sampled data. For this least squares estimation is used, which consists of minimizing.

$$SS = \sum_{i=1}^{n} e_i^{\,2} = \sum_{i=1}^{n} \left(Y_i - a - b_i X_{1i} \ldots\ldots\ldots\ldots - b_m X_{mi}\right)^2 \tag{2}$$

With respect to each of the co-efficients a, b_1…..b_m. This will give k+1 equations from which a, b_1…..b_m. can be obtained. These least squared estimates are the best linear unbiased estimates and hence gives the best linear unbiased estimate of the dependent variable.

$$Y = a + b_1X_1 + b_2X_2 + \dots\dots\dots\dots + b_mX_m \tag{3}$$

The obtained regression model for estimating surface roughness for EN-31 material is,

$$Ra = 2.91e\text{-}2 \times A - 5.04e\text{-}2 \times B + 2.08e\text{-}1 \times C + 1.52e\text{-}2 \times D + 9.071e\text{-}1 \tag{4}$$

The obtained regression model for estimating material removal rate for EN-31 material is,

$$VMRR = 1.12e\text{-}1 \times A - 4.32e\text{-}1 \times B + 5.98e\text{-}1 \times C + 9.66e\text{-}2 \times D + 1.88 \tag{5}$$

The obtained regression model for estimating accuracy for EN-31 material is,

$$Accuracy = 4.68e\text{-}1 \times A - 1.26 \times B + 4.425 \times C + 3.65e\text{-}1 \times D - 13.36 \tag{6}$$

3.2 Group Method of Data Handling

Group method of data handling (GMDH) is a family of inductive algorithms for computer-based mathematical modelling of multi-parametric datasets that features fully automatic structural and parametric optimization of models. GMDH is used in such fields as data mining, knowledge discovery, prediction, complex systems modelling, optimization and pattern recognition. GMDH algorithms are characterized by inductive procedure that performs sorting-out of gradually complicated polynomial models and selecting the best solution by means of the so-called external criterion.

A GMDH model with multiple inputs and one output is a subset of components of the base function *(7)*.

$$Y(x_1, \dots\dots, x_n) = a_0 + \sum_{i=1}^{m} a_i f_i \tag{7}$$

Where f are elementary functions dependent on different sets of inputs, a are coefficients and m is the number of the base function components. In order to find the best solution GMDH algorithm consider various component subsets of the base function *(7)* called partial models. Coefficients of these models estimated by the least squares method. GMDH algorithm gradually increase the number of partial model components and find a model structure with optimal complexity indicated by the minimum value of an external criterion. This process is called self-organization of models. The most popular base function used in GMDH is the gradually complicated Kolmogorov-Gabor polynomial *(8)*.

$$Y(x_1, \dots\dots\dots, x_n) = a_0 + \sum_{i=n}^{n} a_i x_i + \sum_{i=1}^{n}\sum_{j=1}^{n} a_{ij} x_i x_j + \sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{n} a_{ijk} x_i x_j x_k + \dots\dots \tag{8}$$

GMDH is also known as polynomial neural networks and statistical learning networks thanks to implementation of the corresponding algorithms in several commercial software products.

3.3 Artificial Neural Network

A neural network is an artificial representation of human brain that tries to simulate its learning process. ANN is an interconnected group of artificial neurons that uses a mathematical model or computational models for information processing based on a connectionist approach to computation. The artificial neural networks are made of inter connecting neurons which may share some properties of biological neurons. ANN is an information processing paradigm that is inspired by procedure in the biological nervous system. Neural networks are non-linear mapping systems that consist of simple processors which are called neurons, linked by weighed connections. Each neuron has inputs and generates an output that can be seen as the reflection of local information that is stored in connections. The output signal of a neuron is fed to other neurons as input signals via interconnections Fig. 2 shows the network architecture of ANN.

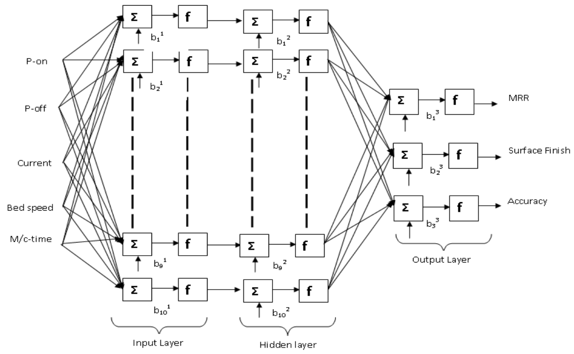

Fig. 2. Network Architecture

The neuron has a bias b, which is summed with the weighted inputs to form the net input n.

$$n = w1,1p1 + w1,2\, p2 + ... + w1,R\, pR + b \tag{9}$$

Various input to the neurons are represented by ‘X_n’. Each of these inputs is multiplied by a connection weighed, represented by ‘W_n’ and added to the bias ‘φ’ to compute activation ‘an’ which is converted into the output ‘On’ via transfer function. Various input to the neurons are represented by ‘X_n’. Each of these inputs is multiplied by a connection weighed, represented by ‘W_n’ and added to the bias ‘φ’ to compute activation ‘an’ which is converted into the output ‘On’ via transfer function.

$$a_n = W_n\, Xn^T + \varphi \tag{10}$$

$$O_n = f\,(a_n) \tag{11}$$

Since the capability of a single neuron is limited, complex functions can be realized by connecting many such neurons to form layers neuron network. The common type of ANN consists of 3 layers viz., Input layer, Hidden layer and Output layer. A layer of input units is connected to a layer of hidden units which is connected to layer of output units. Patterns are presented to the networks via the input layer, which communicates to one or more hidden layers where the actual processing is done via a system of weighed connections. The hidden layers then link to an output layer. A layer is defined as group of parallel neurons without and interaction between them. After conducting the experiment, response values are noted down and analysis has been done. The experiment was conducted in the same environmental condition for all the runs so that environmental noise factors can be minimized. The response variables for EN-31 material are shown in Table 2.

3.3 Prediction of response variables of EN-31 material

The prediction of responses was carried out using MRA, GMDH and Artificial Neural Network Fitting Tool, for various training sets of 50%, 60% and 70% of data is used in GMDH and ANN. When the training is completed, it is necessary to check the network performance and determine if any changes need to be made to the training process, network architecture or the data sets.

Fig. 3, Fig. 4 and Fig. 5 shows the comparison of measured and predicted surface roughness, VMRR and accuracy using MRA, GMDH and ANN. There are different training datasets viz., 50%, 60%, and 70% are used in GMDH and ANN for EN-31 material.

Table 2. Machining performances using L'_{16} orthogonal array

Run	Pulse-on (μs)	Pulse-off (μs)	Current (Amps)	Bed speed (μm/s)	Surface Roughness (μm)	VMRR mm^3/min	Accuracy (μm)
1	16	4	3	20	2.011	5.6076	7
2	16	6	4	25	2.358	5.6774	16
3	16	8	5	30	2.383	5.5443	14
4	16	10	6	35	2.625	6.3811	21
5	20	4	4	30	2.812	8.3791	25
6	20	6	3	35	2.162	5.3819	11
7	20	8	6	20	2.752	5.8081	18
8	20	10	5	25	2.419	5.6596	16
9	24	4	5	35	3.125	10.75	30
10	24	6	6	30	2.879	9.0526	28
11	24	8	3	25	2.184	6.365	10
12	24	10	4	20	2.321	5.1274	14
13	28	4	6	25	2.954	8.6	26
14	28	6	5	20	2.794	6.662	23
15	28	8	4	35	2.865	6.4049	22
16	28	10	3	30	2.196	5.5112	8

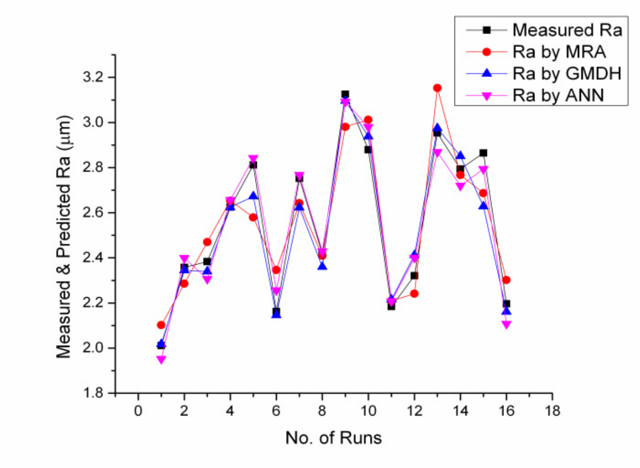

Fig. 3. Comparision of measured and predicted surface roughness usnig MRA, GMDH and ANN

It is observed from the Fig. 3 predicted surface roughness of 70% of the data set exhibits better correlation with the measured surface roughness than 50% and 60% of the data set using ANN when compared to the MRA and GMDH.

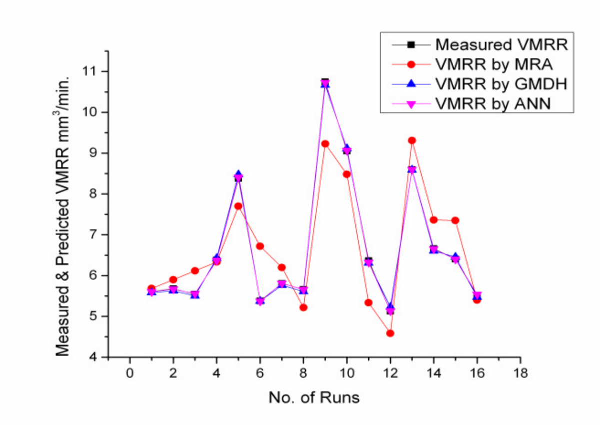

Fig. 4. Comparision of measured and predicted VMRR usnig MRA, GMDH and ANN

From the Fig. 4 predicted VMRR of 70% of the data set exhibits better correlation with the measured VMRR than 50% and 60% of the data set using ANN when compared to the MRA and GMDH.

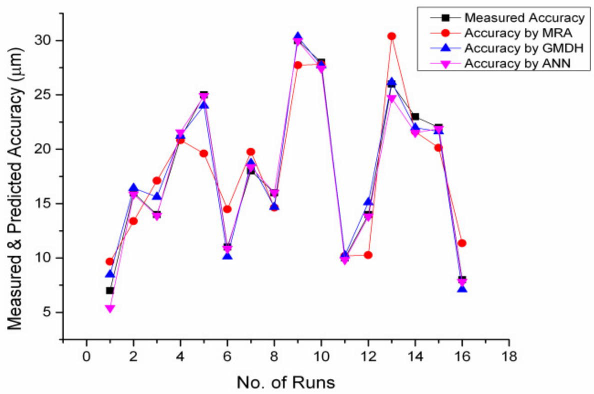

Fig. 5. Comparision of measured and predicted accuracy usnig MRA, GMDH and ANN

It is clearly observed from Fig. 5 predicted accuracy of 70% of the data set exhibits better correlation with the measured accuracy than 50% and 60% of the data set using ANN when compared to the MRA and GMDH.

4. Conclusion

This paper has presented an investigation on the estimation and prediction of machining parameters on accuracy, surface roughness and VMRR in WEDM operations. It was found that, each control factors are affecting the response variables to different extent. We have also seen that multiple regression analysis is a preferred tool for estimating the machining performances EN-31 material. Three different criterion functions of GMDH viz., Regularity (RMS), Unbiased and Combined have been tried for estimation of machining performances EN-31. ANN is used to predict the response variable viz., surface roughness, VMRR and accuracy. Back propagation feed forward neural network (BPNN) and Levenberg–Marquardt algorithm (LMA) are used to build and train the network.

The results from the GMDH show that the regularity criterion function provides good estimation than the other two functions. Different models of GMDH were built by varying the number of data in the training set to 50%, 62.5% and 75% of the total data. It was found that the least error of estimation and best-fit was found for 62.5% of data in training set for surface roughness and 75% of data in training set for VMRR and accuracy. Comparison of the three theoretical methods for estimation of machining performances, it was found that, artificial neural network fitting function has an edge over MRA and GMDH method. It is observed that neural network trained with 70% of the data in training set gives good prediction results when compared to the 50% and 60% of data in training set. Thus, predicted response variables of 70% training set correlates well with the measured response variables. ANN function gave better prediction than MRA and GMDH.

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